

## Economics 696F, Homework 5

Due Tues, April 4, 2006, by end of day

Consider the probit model:

$$\Pr(y_i = 1|x_i) = \Phi(\alpha + \beta x_i),$$

where  $y_i$  and  $x_i$  are scalars, and conditional on  $\alpha, \beta, x$ , the  $y_i$  are independent.

The data for this exercise are available in ascii format in the file `hw5.dat`. (The first column of `hw5.dat` contains the vector of observations on  $y_i$ , and the second column contains the vector of observations on  $x_i$ .)

Consider two priors for  $\alpha, \beta$ :

$$p(\alpha, \beta) \propto 1,$$
$$p(\alpha, \beta) \propto \exp\left(-\frac{100}{2}\beta^2\right),$$

1. Calculate the marginal posterior  $p(\beta|y, x)$  under the two prior specifications. To perform the calculations, discretize the parameter space for  $\alpha$  as

$$\alpha \in \{-10.0, -9.9, \dots, 9.9, 10.0\}.$$

Likewise, discretize the parameter space for  $\beta$  as

$$\beta \in \{0, .01, .02, \dots, .49, .50\}.$$

See below for more information on discretization.

Plot the two marginal posterior distributions on one plot, and discuss their similarities and/or differences.

2. Write a data augmentation algorithm, assuming a uniform prior on both  $\alpha$  and  $\beta$ , to simulate the posterior distribution of  $(\alpha, \beta)$ . Initialize the parameters at  $(0, 0)$  and run the algorithm for 500 iterations. Save the draws for  $\alpha$  and  $\beta$ ; you do not need to save the draws for any latent variables for the purposes of this exercise.

Plot  $\alpha$  and  $\beta$  over time and discuss whether it appears that they have “converged.” Provide an approximate posterior mean and posterior variance for  $\beta$ . Discard the first 100 iterations and plot a histogram of the last 400 draws for  $\beta$ .

### Discretization Method

Suppose we have a likelihood  $p(z|\theta)$  and a prior  $p(\theta)$  on some parameter space  $\Theta$ .

One possibility is to discretize the parameter space  $\Theta$ . Suppose that  $\Theta = \{\theta_1, \dots, \theta_K\}$ . Then we would have

$$p(\theta_j|z) = \frac{p(\theta_j)p(z|\theta_j)}{\sum_{k=1}^K p(\theta_k)p(z|\theta_k)}. \quad j = 1, \dots, K.$$

The sum in the denominator only needs to be done once, and can be implemented on a computer since  $\Theta$  is finite. Likewise, calculating expectations with respect to the posterior distribution would only involve finite sums, with the  $p(\theta_j|z)$  used as weights.